Predicted deep-sea coral habitat suitability for Alaskan waters

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Abstract

Predictive habitat models for deep-sea corals in Alaskan waters, including the U.S. Exclusive Economic Zone, were developed for NOAA-NMFS' Office of Habitat Conservation. Models are intended to aid in future research/mapping efforts, assess potential coral habitat suitability both within and outside existing bottom trawl closures (i.e. Essential Fish Habitat (EFH), Habitat Areas of Particular Concern (HAPC), Habitat Conservation Areas (HCA), etc.)). Deep-sea coral habitat suitability was modeled at ~ 700 m x 700 m spatial resolution using a variety of physical, chemical and environmental variables known or thought to influence the distribution of deep-sea corals. Maxent models identified slope, temperature, salinity and depth as important predictors for most deep-sea coral taxa. Large areas of highly suitable deep-sea coral habitat were predicted both within and outside of existing bottom trawl closures. Predicted habitat suitability results are not meant to identify coral areas with pin point accuracy and probably over predict actual coral distribution due to model limitations and unincorporated variables (i.e. substrate) that are known to limit their distribution. Predicted habitat results should be used in conjunction with multibeam bathymetry, geologic maps, and other tools to guide future research efforts to areas with the highest probability of harboring deep-sea corals. Field validation of predicted habitat is needed to quantify model accuracy, particularly in areas that have not been sampled. Model accuracy would improve with the addition of coral presence and absence data from field validation efforts currently underway.

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Introduction

Stone and Shotwell (2007) reviewed the state of deep coral ecosystems in Alaskan waters and reported Alaskan waters harbor highly diverse and abundant coral communities. These communities include species from six major taxonomic groups: true or stony corals (Order Scleractinia), black corals (Order Antipatharia), true soft corals (Order Alcyonacea) including the stoloniferans (Suborder Stolonifera), sea fans (Order Gorgonacea), sea pens (Order Pennatulacea), and stylasterids (Order Anthoathecatae). One hundred and forty one unique coral taxa have been documented from Alaskan waters and include 11 species of stony corals, 14 species of black corals, 15 species of true soft corals (including six species of stoloniferans), 63 species of gorgonians, 10 species of sea pens, and 28 species of stylasterids. All corals found in Alaska are azooxanthellate and satisfy all their nutritional requirements by the direct intake of food. They are ahermatypic or non-reef building corals, but many are structure forming. The degree to which they provide structure depends on their maximum size, growth form, intraspecific fine-scale distribution, and interaction with other structure-forming invertebrates.

Stone (2006) reported the majority of commercially fished species in Alaskan waters have associations with coral and sponge habitat at some point in their life cycle. These habitats provide nursery grounds, spawning areas and shelter for many fish and associated species. Sampling effort for deep-sea corals varies geographically due to the large size of the EEZ and distribution of fishery and trawl survey effort. Some of the most important coral areas (i.e. Western and Central Aleutians) are not well sampled and are prime candidate areas for predictive habitat modeling.

Predictive habitat suitability modeling is a tool that is rapidly being adopted to identify areas with the highest probability of harboring deep-sea corals in areas that have not been visited and can enhance our knowledge of the factors that control the distribution of these organisms (Bryan & Metaxas 2007, Davies et al. 2008, Guinan et al. 2009, Tittensor et al. 2009, Davies and Guinotte 2011, Yesson et al. 2012, Guinotte and Davies 2012). Modeling approaches have the potential to significantly improve our knowledge of the distribution of deep-sea corals by extrapolating species distributions from presence data and a range of environmental variables.

These methods can make significant and cost-effective contributions to scientific research, conservation, and management of deep-sea resources. Several studies have focused on improving small-scale predictive habitat models by integrating digital terrain variables derived from multibeam bathymetry (e.g. Wilson et al. 2007, Howell et al. 2011). While local-scale modeling produces valuable data on species distributions in localized areas (1-100 km^2), it often requires intensive sampling effort and is often of limited use in the identification of unknown habitat for cruise planning, management and conservation initiatives. Broad, regional-scale models are needed to predict habitat suitability for corals in areas that have not been surveyed and have to be accurate enough to guide a research vessel towards a clearly defined area where sampling can be targeted (Davies and Guinotte 2011, Guinotte and Davies 2012).

The predictive habitat suitability modeling effort for deep-sea corals described in this report focuses on U.S. EEZ waters off the coast of Alaska. The objectives of this research effort are 1) develop predictive habitat suitability models at the highest possible spatial and taxonomic resolution, 2) use model results, in addition to other tools, to help guide field research efforts to areas with the highest probability of harboring deep- sea corals, and 3) integrate model results with existing bottom trawl closures (i.e. essential fish habitat (EFH) area closures) to determine high probability habitat areas that remain at risk from human activity.

Methods

Coral presence data

Coral distribution data were gathered from two sources: NOAA Fisheries (Robert Stone) and the Smithsonian Institute's National Museum of Natural History (Stephen Cairns). These records were obtained from a variety of gear types: remotely operated vehicles (ROVs), manned submersibles, cameras, grabs and bottom trawls. Coral locations were eliminated if they matched the following criteria: 1) records were collected as bottom trawl bycatch, 2) the taxonomy of coral records was uncertain to family, and 3) if more than one coral record of the same taxon (order or suborder) was located within the same 700 m grid cell. Trawl bycatch records were eliminated as they have inherent spatial and taxonomic accuracy issues, creating uncertainties that stem from both the method in which they were collected and the taxonomic knowledge of observers on fishing vessels. Bottom trawls can be several kilometers in length and it can be difficult if not impossible to determine the position of the actual coral occurrence (Bellman et al. 2005).

There are several issues which prevented models from being performed at the species level: 1) taxonomic disagreement, 2) varying degrees of taxonomic knowledge among observers and collectors, and 3) many coral presences are documented without a sample being collected to conclusively determine coral taxonomy to species. These are valid concerns and similarly noted in global models for octocoral habitat suitability (Yesson et al. 2012) and regional models for the U.S. West Coast (Guinotte and Davies 2012). For these reasons coral records were grouped and modeled at the suborder and order levels. Suborders for which coral presence data were obtained included Alcyoniina, Calcaxonia, Filifera, Holaxonia, Scleraxonia, Stolonifera. Order level data included Antipatharia and Scleractinia. A total of 928 coral records were retained for analysis (Table 1). Numerous presences records were collected for Suborders Sessiliflorae and Subselliflorae (sea pens), but were not modelled. A separate model was created specifically for 40 locations of coral and sponge gardens documented in the Central Aleutians in hopes of identifying areas where other gardens might exist. Gardens are areas of exceptionally high abundance and diversity of deep-sea corals and sponges.

Table 1. Coral records retained for habitat suitability modeling by taxon.

Taxa	**Records retained**
Order	
Antipatharia	44
Scleractinia	72
Suborder	
Alcyoniina	71
Calcaxonia	259
Filifera	250
Holaxonia	149
Scleraxonia	66
Stolonifera	17
Total	928

Bathymetry development

To model the Alaskan shelf, a composite bathymetry was created consisting of the Southern Alaska Coastal Relief Model, a 24 arc-second digital elevation model (Lim et al, 2011). This bathymetry collates sounding data from a variety of different sources, including high-resolution multibeam data, digitised nautical charts, the National Oceanographic Service hydrographic survey data, track line data and satellite altimetry from the ETOPO1 sensor (Lim et al., 2011). These data were used to interpolate a continuous surface that covered 170° to 230° and 48.5° to 66.5° N using a tight spline tension approach within MB-System. As this grid does not cover the whole of the Alaska exclusive economic zone, missing areas were filled using the global bathymetric product SRTM30 that is available at a 30 arc second resolution (Becker et al., 2009).

Environmental variable production

Several terrain attributes were extracted from the composite bathymetry data (Table 2) following techniques and algorithms described in Wilson et al (2007). Individual approaches are described within the footnote of Table 2, however, briefly the extraction process and description of each variable is described here. Bathymetric position index (BPI) is an approach to determine topographical features based on their relative position within a neighbourhood, and can be calculated over fine or broad scales to capture smaller or larger terrain features respectively. This calculation has been developed into an ArcGIS tool by Wright et al. (2005). Slope was calculated using DEM Tools for ArcGIS developed by Jenness (2012), in particular the 4-cell method of calculating slope, which is accepted as the most accurate approach (Jones 1998). In this manuscript, slope is defined as the gradient in the direction of the maximum slope. Curvature attempts to describe terrain features and may provide an indication of how water would interact with the terrain. In this manuscript, plan and tangential curvature can describe how water would converge or diverge as it flows over relief, whilst profile curvature describes how water would accelerate or decelerate as it flows over relief (Jenness 2012). Aspect is defined as the direction of maximum slope and was converted to continuous radians following Wilson et al. (2007). Rugosity, terrain ruggedness index and roughness all generally describe the variability of the relief of the seafloor (Wilson et al. 2007). Rugosity is defined as the ratio of the surface area to the planar area across a neighbourhood of a central pixel (Jenness 2012). Terrain ruggedness index is defined as the mean difference between a central pixel and its surrounding cells and roughness which is the largest inter-cell difference of a central pixel and its surrounding cell (Wilson et al. 2007).

The processes used to create the remaining environmental data for the Alaskan shelf closely followed approaches presented in Davies and Guinotte (2011) and Guinotte and Davies (2012). The underlying data that were used to create the continuous layers were acquired from sources that included ship-based CTD casts, satellites, and from global climatologies such as World Ocean Atlas (Table 2). The majority of source data was available as gridded datasets partitioned into standardized depth-bins ranging from 0 to 5500 m. Other data were available only as single layers from the surface (e.g. surface primary productivity) (Table 2). Converting depth-binned datasets into representations of seafloor conditions involved several computer intensive processes that were conducted within a series of Python scripts. Firstly, each depth-bin of the gridded data is extracted into a single layer and interpolated at a higher spatial resolution (usually 0.1°) using inverse distance weighting. The interpolation was required to reduce gaps that appear between adjacent depth bins due to a lack of overlap when extrapolated to the bathymetry. Each of these layers was then resampled to match the extent and resolution of the bathymetry with no further interpolation. Secondly, these layers were resampled to match the extent and cell resolution of the bathymetry. Thirdly, each resampled depth-bin was clipped by the area of seafloor that was available at that particular depth. Each bin did not overlap and all were merged to produce a continuous representation of the variable on the seafloor.

Table 2. Environmental, physical, and chemical layers developed for this study. Notes indicate particular analysis or treatment of data.

Variable name	Units	Reference
Terrain variables[1]		
Bathymetry	m	
Bathymetric Position Index – Broad [3,4]		Wright et al. (2005)
Bathymetric Position Index – Fine [4,5]		Wright et al. (2005)
Slope [6]	Degrees	Jenness (2012)
Curvature – Profile [7]		Jenness (2012)
Curvature – Plan [8]		Jenness (2012)
Curvature – Tangential [9]		Jenness (2012)
Aspect	Degree	Jenness (2012)
Aspect – Eastness [10,11]		
Aspect – Northness [10,12]		
Rugosity [13]		Jenness (2012)
Terrain Ruggedness Index [14]		Wilson et al. (2007)
Topographic Position Index [14]		Wilson et al. (2007)
Roughness [14]		Wilson et al. (2007)
Environmental variables		
Dissolved oxygen [15]	ml l^{-1}	Garcia et al.(2006a)
Nitrate [15]	μmol l^{-1}	Garcia et al. (2006b)
Omega aragonite [15]	Ω_{ARAG}	Steinacher et al. (2008)
Omega calcite [15]	Ω_{CALC}	Steinacher et al. (2008)
Phosphate [15]	μmol l^{-1}	Garcia et al. (2006b)
Salinity [15]	pss	Boyer et al. (2005)
Silicate [15]	μmol l^{-1}	Garcia et al. (2006b)
Temperature [15]	°C	Boyer et al. (2005)

[1]All terrain variables were derived from CRM bathymetry. [2] For visualisation purposes only. [3] Constructed using annulus settings of 1 & 25 (factor of 250). [4] Positive values indicate relief such as peaks and crests, negative values indicate troughs or depressions. [5] Constructed using annulus settings of 1 & 5 (factor of 50). [6] Calculated using the 4 cell method. [7] Longitudinal curvature in Jenness (2012) and defined as "Longitudinal curvatures are set to positive when the curvature is concave (i.e. when water would decelerate as it flows over this point). Negative values indicate convex curvature where stream flow would accelerate." Zero indicates an undefined value. [8] Defined in Jenness (2012) as "Plan curvatures are set to positive when the curvature is convex (i.e. when water would diverge as it flows over this point). Negative values indicate concave curvature where stream flow would converge." Zero indicates an undefined value. [9] Defined in Jenness (2012) as "Tangential curvatures are set to positive when the curvature is convex (i.e. when water would diverge as it flows over this point). Negative values indicate concave curvature where stream flow would converge." Zero indicates an undefined value. [10] Calculated in ArcGIS 10. [11] Modified calculation from Wilson et al. (2007) using Sin((Aspect * π) /180), to produce 1 = east and -1 = west orientation. [12] Modified calculation from Wilson et al. (2007) using Cos((Aspect * π) /180), to produce 1 = north and -1 = south orientation. [13] Calculated in Benthic Terrain Modeler, Wright et al. (2005), flat areas exhibit values of 1, with high relief areas have higher values but very rarely exceed 3. [14] Calculated using GDAL DEM Tool. Values at zero indicate flat areas, higher values indicate rough and variable terrain. [15] Variable creation process followed the Davies and Guinotte (2011) upscaling approach.

Variable selection

Variables were selected based on a literature search of environmental, physical, and chemical factors known or thought to influence deep-sea coral growth and survival. Temperature, salinity, carbonate chemistry, depth, and topographic complexity have been shown to be strong predictors of coral distribution in recent deep-sea modeling efforts (Guinotte et al 2006, Tittensor et al 2009, Davies and Guinotte 2011, Yesson et al. 2012, Davies and Guinotte 2012). Covariation between environmental datasets is a complication that must be addressed in many predictive modeling efforts. Environmental datasets used in this analysis were assessed for covariation in correlation matrices. Although Maxent is reasonably robust with respect to covariation, an *a priori* variable selection process was used to reduce covariation by removing variables that were highly correlated and likely to adversely affect final predictions. Covariation was assessed using correlation matrices in R. Strong correlations between variables (>0.7) were addressed by omitting one of the environmental variables. The importance of each variable in the model was assessed using a jack-knifing procedure that compared the contribution of each variable (when absent from the model) with a second model that included the variable. The final habitat suitability maps were produced by applying the calculated models to all cells in the study region, using a logistic link function to yield a habitat suitability index (HSI) between zero and one (Phillips et al. 2006).

Modeling Methods

Maxent version 3.2.1 (http://www.cs.princeton.edu/~schapire/maxent) was used to model predicted deep-sea coral distributions for the U.S. West Coast. Maxent (maximum entropy modeling) consistently outperforms other presence-only modeling packages including Ecological Niche Factor Analysis (ENFA) (Elith et al 2006, Tittensor et al. 2009). Presence-only modeling is one of the only methods available for modeling species distributions in the deep sea because documented absence data is sparse. Maxent's underlying assumption is the best way to determine an unknown probability distribution is to maximize entropy based on constraints derived from environmental variables (Phillips et al 2006). Default model parameters were used as they have performed well in other studies (a convergent threshold of 10^{-5}, maximum iteration value of 500 and a regularization multiplier of 1, (Phillips and Dudik 2008). Model accuracy between the test data and the predicted suitability models was assessed using a threshold-independent procedure that used a receiver operating characteristic (ROC) curve with area under curve (AUC) for the test localities and a threshold-dependent procedure that assessed misclassification rate. To calculate validation metrics, the presence data was randomly partitioned to create 75% training and 25% test datasets, with test data used to calculate validation metrics. With presence-only data, Phillips et al. (2006) define the AUC statistic as the probability that a presence site is ranked above a random background site. In this situation, AUC scores of 0.5 indicate that the discrimination of the model is no better than random and the maximum achievable AUC value is 1. In this study, all models had AUC scores > 0.9.

There is ongoing debate regarding the interpretation of Maxent's logistic prediction values (0–1) for habitat suitability (Hernandez et al. 2006, Lobo et al. 2008). Several studies have defined a binary threshold, which states that a species is likely to be found in an area with a habitat suitability value above a given threshold, but not likely to be found below it (Pearson et al. 2007, Raes et al. 2009, Rebelo & Jones 2010). The assumption with a 10^{th} percentile cutoff is that 10 % of the presence data may occur in areas where the species is absent due to positioning errors or lack of resolution in environmental data, and as such, omits the suitability values below the highest of the 10% of records.

Results and Discussion

Species niches

From the suite of environmental variables available, an *a priori* variable selection process identified eight variables that were likely to influence the probability of species presence (temperature, salinity, particulate organic carbon, depth, calcite saturation state, slope, rugosity, and silicate) (Table 3). Silicate was only included in the predictive model for the coral and sponge gardens as sponges use silicate to build their internal structures. The jack-knife of variable contribution showed depth, temperature, and salinity were the strongest predictors for Suborder Filifera, Suborder Holaxonia, Suborder Scleraxonia, Order Scleractinia, all taxa combined, and the coral and sponge gardens. Depth, rugosity, and slope were the strongest predictors for Suborder Alcyoniina and Order Antipatharia. Particulate organic carbon, salinity, and temperature were the strongest predictor variables for Suborder Calcaxonia. The three strongest predictors for Suborder Stolonifera were depth, calcite saturation state, and temperature.

Three highly correlated variables (depth, calcite saturation state, and temperature) were retained due to ecophysiological importance and the strength of their contributions. This must be interpreted with caution as these layers covary and may contain similar information, which can artificially inflate variable contribution scores. However, the test AUC scores for models generated with a single variable reinforced that these variables were top predictor variables regardless of covariation. Suborder Stolonifera was the only group to have calcite saturation state in the top three predictor variables indicating some species within this Suborder could be sensitive to changes in carbonate chemistry. It was possible to gain insight into the species niches and the factors that are most important in driving their distribution by intersecting the distribution of coral records with the environmental, physical, and chemical layers (Figures 1 and 2). The bean plots show the distribution of the parameters for all coral records by taxa across the study area.

Model evaluation and habitat maps

The coral habitat models performed well across all the metrics used to validate the modeled outputs. All bar two AUC scores were > 0.9 and were significantly different from that of a random prediction of AUC = 0.5 (Wilcoxon rank-sum test, $p<0.01$). High AUC scores were supported by high test gains and low omission rates across many of the modeled taxa indicating most presences were accounted for in the predictions (Table 3). Figures 3-13 show the distribution of predicted deep-sea coral habitat across the North Pacific basin. The majority of predicted habitat (with the highest probabilities) occurs in the Aleutian Islands, Bering Shelf, Gulf of Alaska seamounts, and the Fjord region and shelf break of Southeast Alaska. Warmer colors indicate higher probability of coral habitat being present. Figure 8 shows predictive habitat model results (coral and sponge gardens) for the Western Aleutians. This figure highlights the utility of high resolution model results for assessing the effectiveness of existing bottom trawl closures via Essential Fish Habitat (EFH) and Habitat Areas of Particular Concern (HAPC) designations. These results can be used to help guide future EFH and HAPC reviews conducted by the North Pacific Fishery Management Council.

Model validation and targeting areas for field operations

Field validation of modeled habitat is needed to 1) Assess the accuracy of model predictions. 2) Refine models by identifying false positives and negatives. And 3) Gauge the utility of these modeling methods for identifying deep-sea coral habitat in unsurveyed areas. Model accuracy would improve with the addition of coral presence and absence data collected from field validation efforts. The predicted habitat suitability results presented here are not meant to identify coral occurrences with pin point accuracy and are unlikely to achieve this based on currently available data. They are more useful for directing research effort to areas that have the highest probability of supporting deep-sea corals and identifying low probability areas that could be avoided to maximize time spent in high probability areas. Broad-scale predictive habitat results should be used in conjunction with multibeam surveys, geologic substrate maps and other tools to determine the most likely areas for harboring deep-sea corals. One additional complication for field validation efforts using these predictions are the current technological limitations of survey vehicles and equipment (i.e. ROVs, submersibles, drop cameras, etc.). The distribution of deep-sea corals within a single grid cell of these models (700 m x 700 m) could be patchy (Wilson, 1979) and could be missed on vehicle transects with limited range and narrow fields of view. To address this limitation and to improve the probability of locating undiscovered coral areas, research ships should first use multibeam surveys (in high probability areas) to identify substrate characteristics that can support deep-sea coral growth or identify corals (e.g. emergent hard substrata, coral rubble).

Table 3. Validation statistics and jack-knife analysis of variable contributions to the models. Higher values for the regularized training gain of the jack-knife test indicates greater contribution to the model for a variable (these values are not directly comparable between the different taxa). Test AUC numbers in parentheses are the standard deviation of the Test AUC scores. The top three variables are highlighted in bold for each taxon, both for the jack-knife variable contribution and test AUC values for Maxent models generated using a single variable.

	All Taxa	Alcyoniina	Antipatharia	Calcaxonia	Filifera	Holaxonia	Scleractinia	Scleraxonia	Stolonifera	coral gardens
Validation statistics										
Test AUC	0.946 (0.008)	0.907 (0.018)	0.986 (0.003)	0.973 (0.005)	0.979 (0.004)	0.975 (0.008)	0.959 (0.014)	0.943 (0.021)	0.931 (0.057)	0.997 (0.001)
Test gain	2.05	1.172	2.794	2.701	2.955	2.735	2.353	2.204	2.518	4.623
10th percentile training presence	0.186	0.156	0.128	0.2	0.186	0.181	0.063	0.151	0.205	0.239
Maximum test sensitivity plus specificity	0.187	0.141	0.177	0.181	0.052	0.124	0.02	0.184	0.751	0.169
Jack-knife of variable importance (jack of regularized training gain)										
Depth	**1.1696**	**0.7472**	**1.2147**	1.12	**1.7338**	**1.5152**	**1.2342**	**1.7339**	**0.7868**	**1.8152**
Rugosity	0.6121	**0.9291**	**2.5147**	0.9551	0.6135	1.1795	0.9671	1.209	0.339	1.6961
Calcite Saturation State	1.0733	0.667	0.4633	0.976	1.5611	1.3731	0.97	1.0577	**0.603**	1.7178
Particulate Organic Carbon	1.0526	0.7069	0.5727	**1.1313**	1.5365	1.2021	1.1284	1.0868	0.081	1.5259
Salinity	**1.3659**	0.6285	1.1448	**1.3835**	**2.1153**	**1.927**	**1.3444**	**1.8518**	0.0426	**2.2849**
Slope	0.5077	**0.881**	**2.3889**	0.8301	0.5301	1.0151	0.7692	1.0342	0.3396	1.3084
Temperature	**1.4642**	0.3076	0.5528	**1.393**	**2.2755**	**1.9407**	**1.6947**	**1.6688**	**0.7885**	**2.4752**
Silicate	**null**	**null**	**null**	**null**	**null**	**null**	**null**	**null**	**null**	1.7275
Test AUC for a single variable										
Depth	0.8917	**0.819**	0.8127	0.8956	**0.9432**	0.9068	0.853	**0.8956**	0.7511	0.9472
Rugosity	0.7778	0.8131	**0.9815**	0.8734	0.7949	0.8237	**0.9201**	0.8643	**0.9358**	0.9098
Calcite Saturation State	0.8817	**0.8245**	0.6998	0.8733	0.9333	0.8872	0.821	0.8476	0.8023	**0.9839**
Particulate Organic Carbon	**0.8945**	**0.8212**	0.7857	**0.9023**	0.927	**0.9169**	0.8159	0.8294	**0.8828**	0.9007
Salinity	**0.9088**	0.8064	**0.8213**	**0.9068**	**0.9652**	**0.937**	**0.8773**	**0.9085**	0.7336	**0.9718**
Slope	0.761	0.7885	**0.9772**	0.8566	0.7452	0.7964	**0.8938**	0.8354	**0.9478**	0.8523
Temperature	**0.9187**	0.7422	0.6648	**0.9113**	**0.9638**	**0.916**	0.8238	**0.8824**	0.8246	**0.9883**
Silicate	**null**	**null**	**null**	**null**	**null**	**null**	**null**	**null**	**null**	0.9507

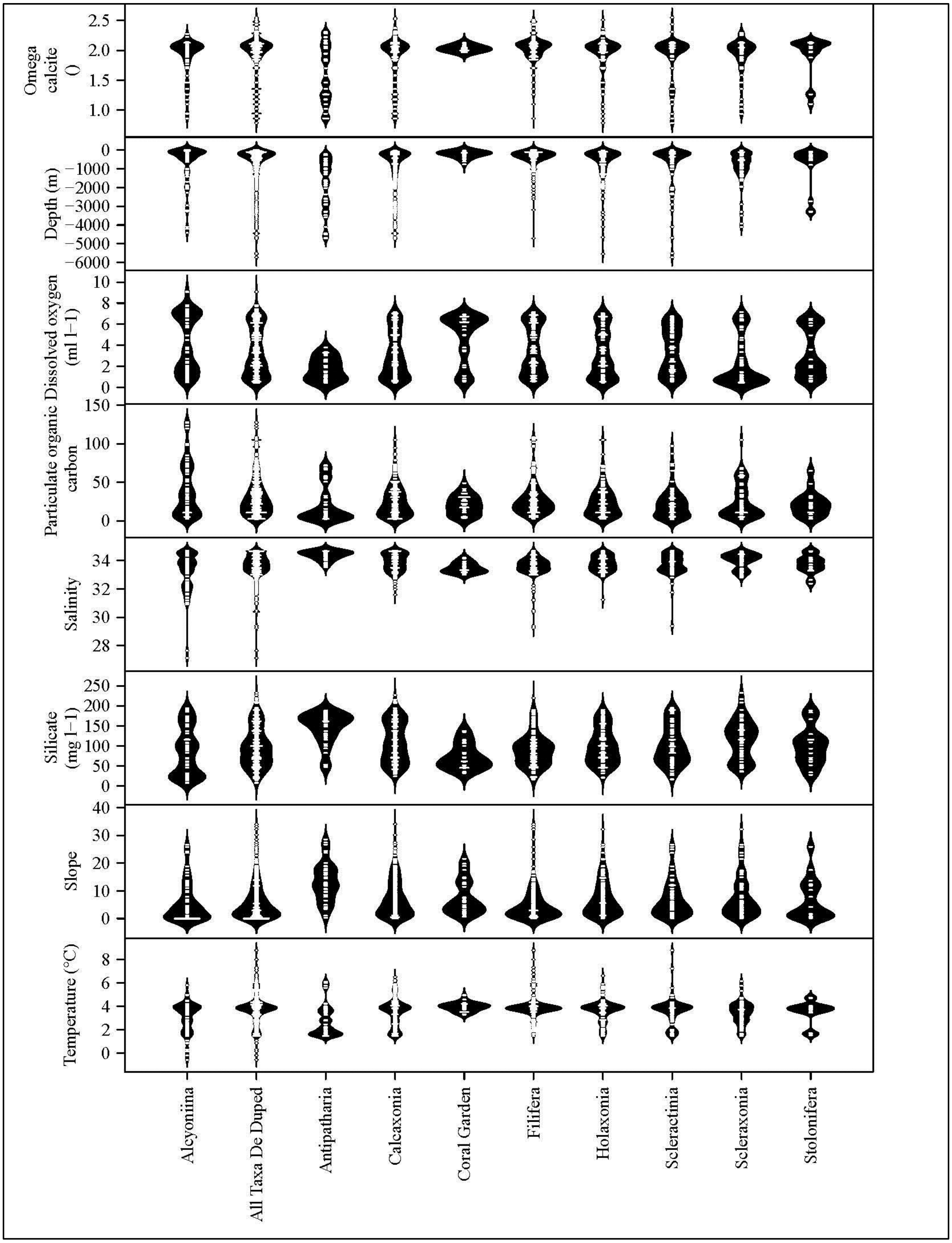

Figure 1. Bean plots of coral presences intersected with the environmental, physical and chemical variables used in the models (the small lines in the center of each bean shows individual coral presence points). The bean itself is a density trace that is mirrored to show as a full bean (Kampstra 2008).

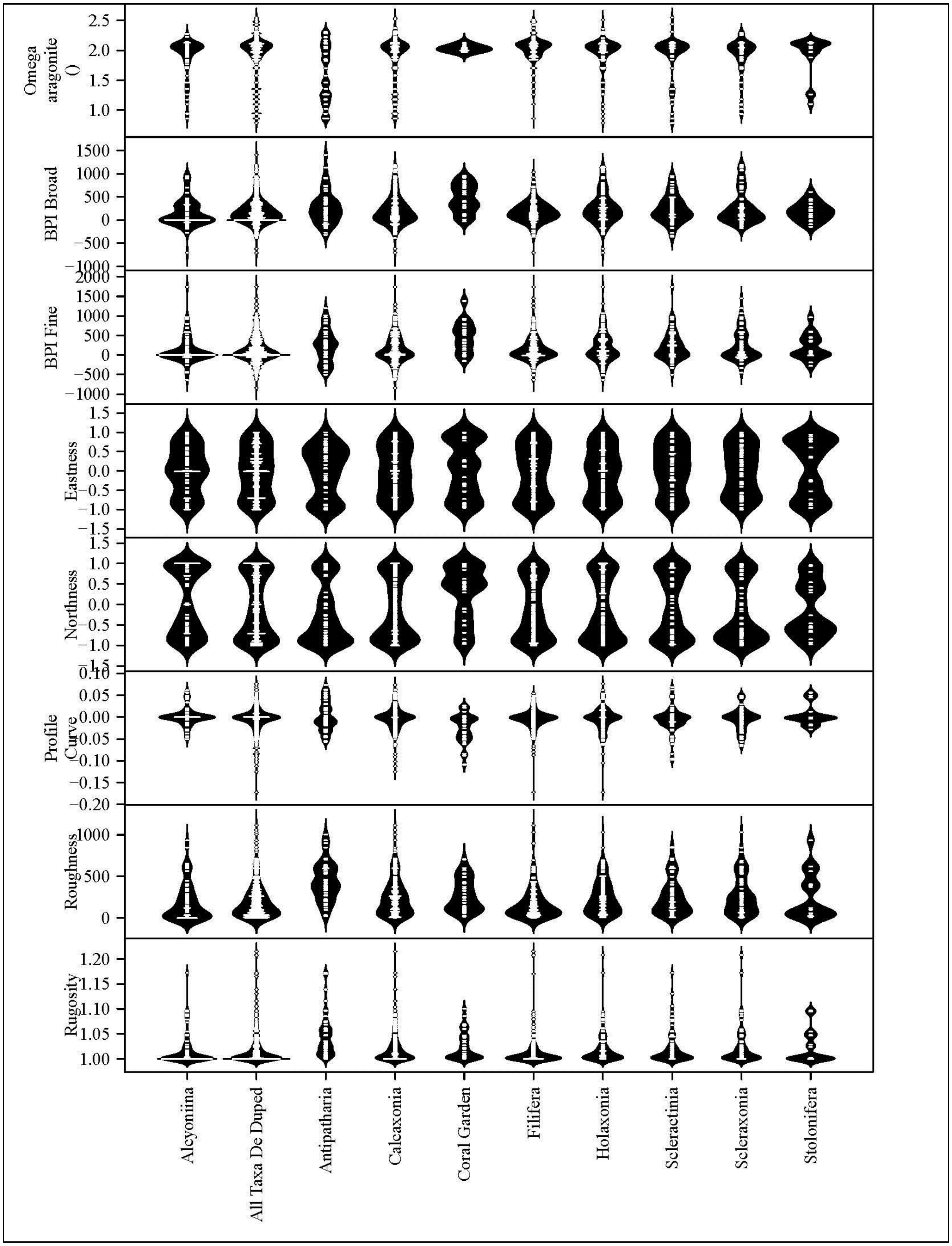

Figure 2. Bean plots of coral presences intersected with the environmental, physical and chemical variables used in the models (the small lines in the center of each bean shows individual coral presence points). The bean itself is a density trace that is mirrored to show as a full bean (Kampstra 2008).

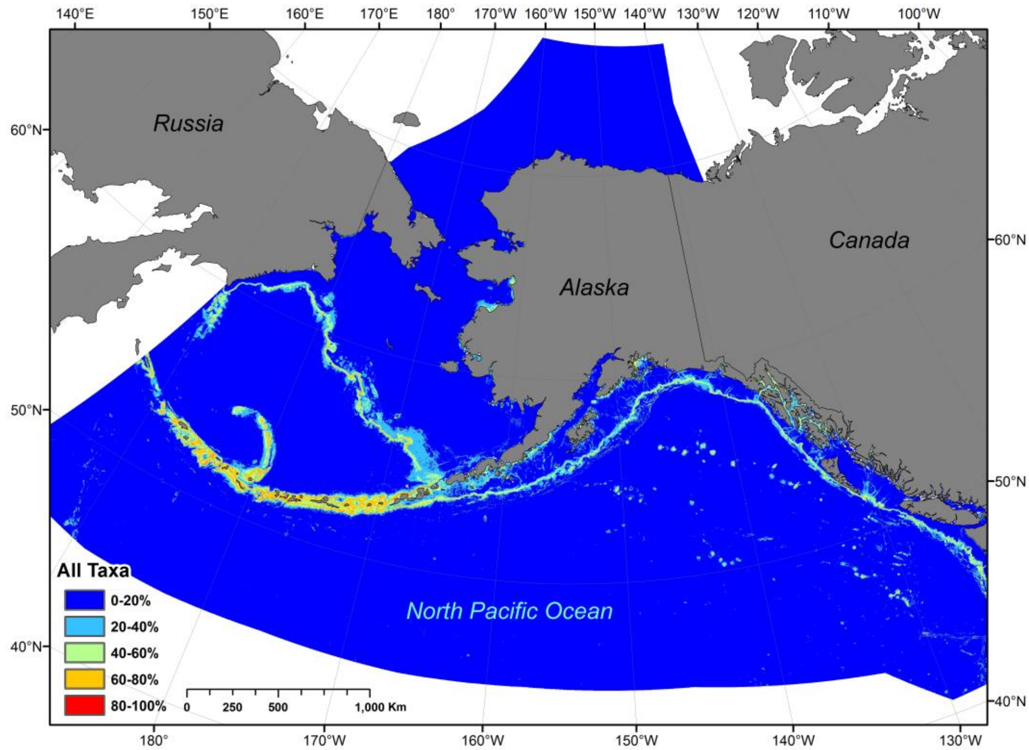

Figure 3. Maxent predictive habitat model results for all deep-sea coral taxa combined.

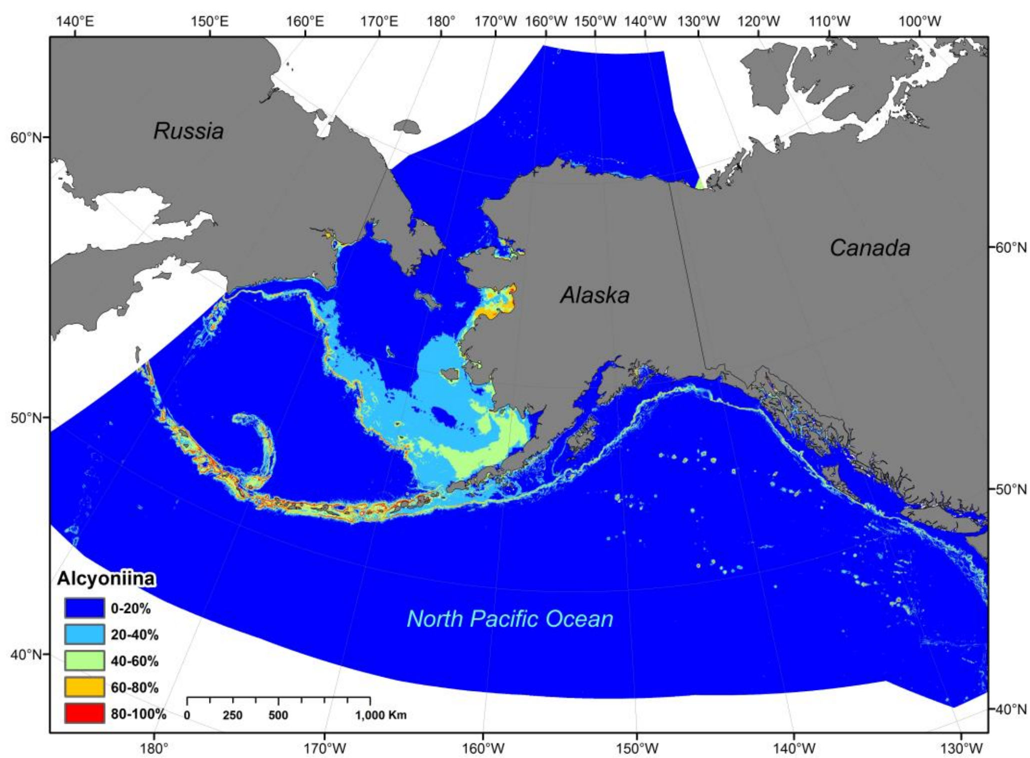

Figure 4. Maxent predictive habitat model results for Suborder Alcyoniina.

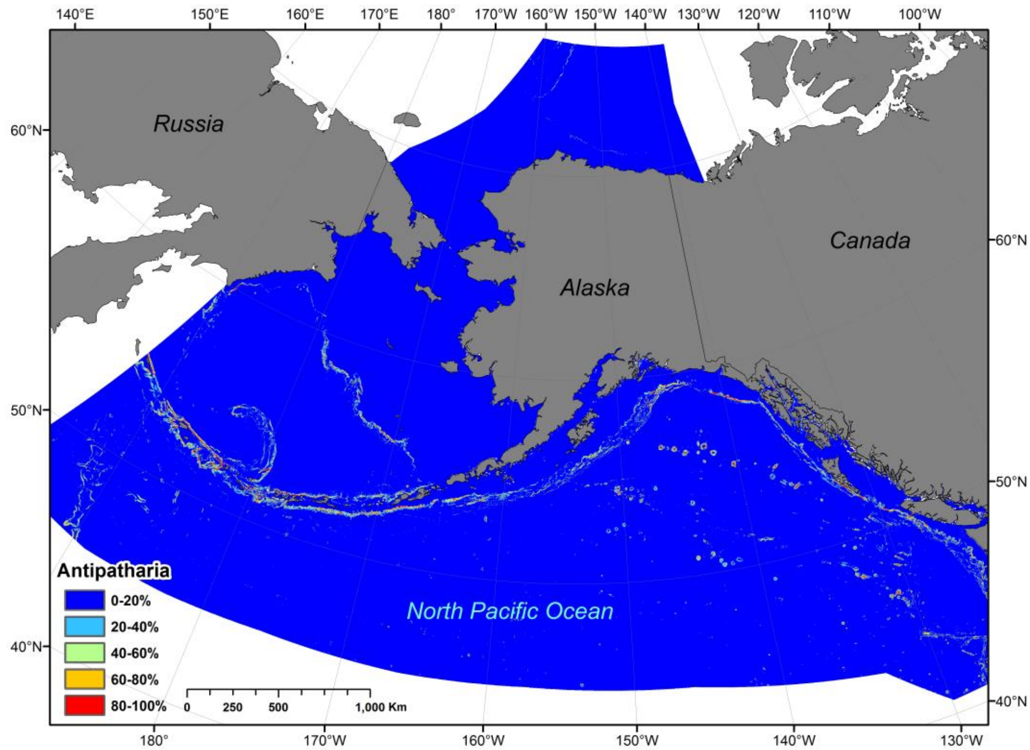

Figure 5. Maxent predictive habitat model results for Order Antipatharia.

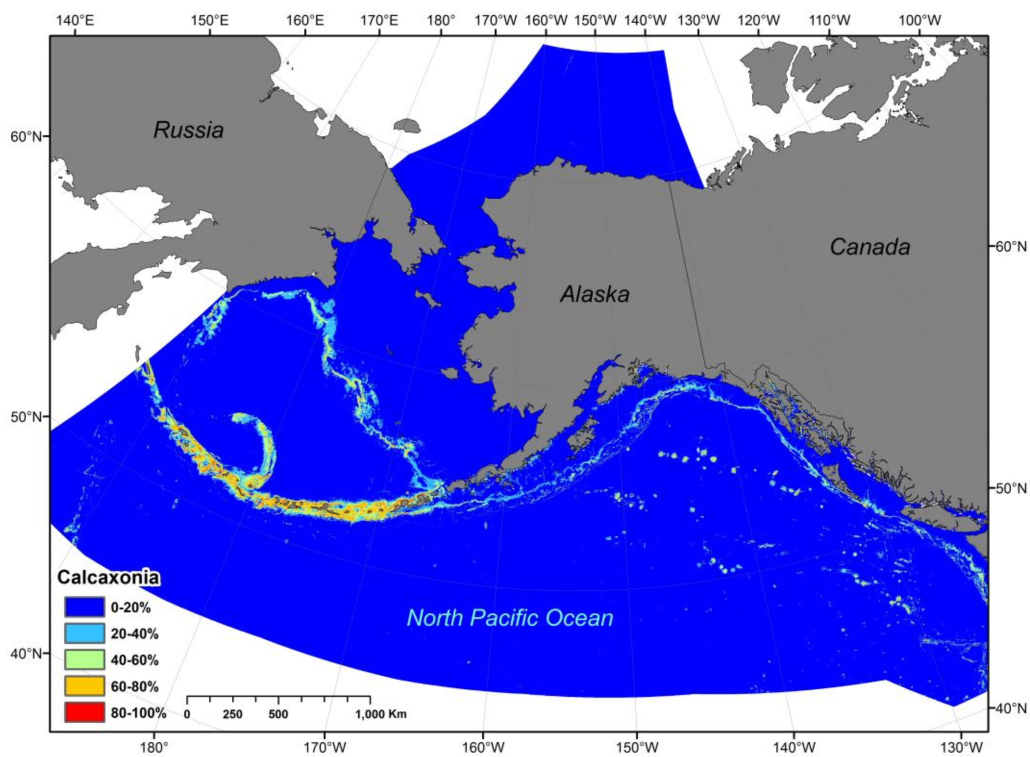

Figure 6. Maxent predictive habitat model results for Suborder Calcaxonia.

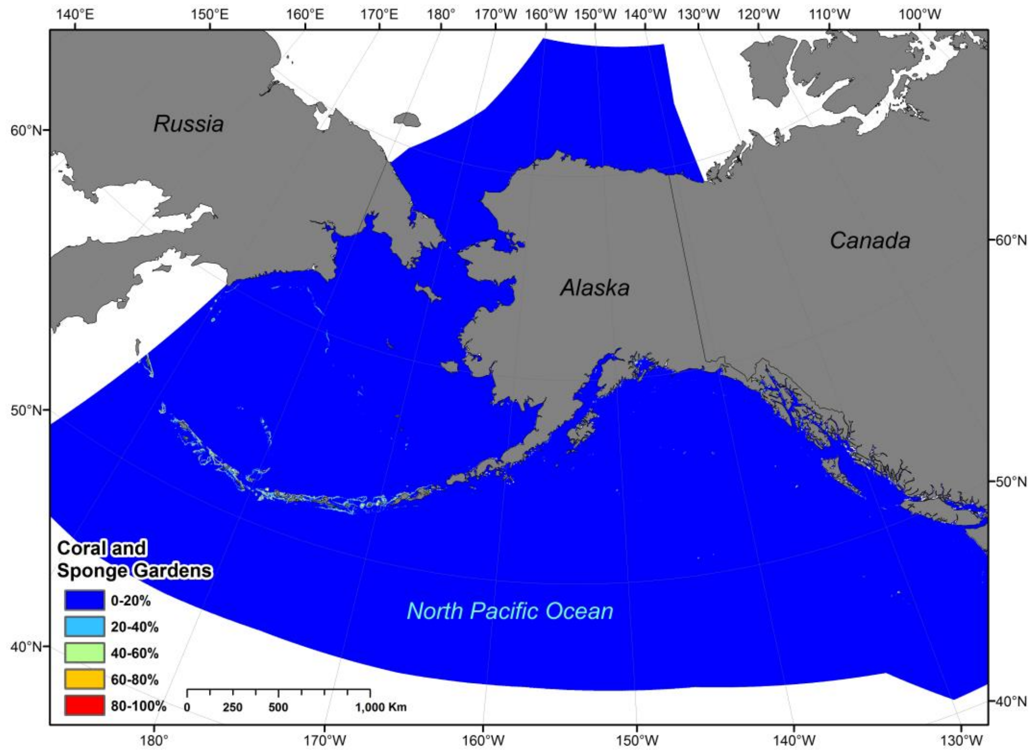

Figure 7. Maxent predictive habitat model results for coral and sponge gardens.

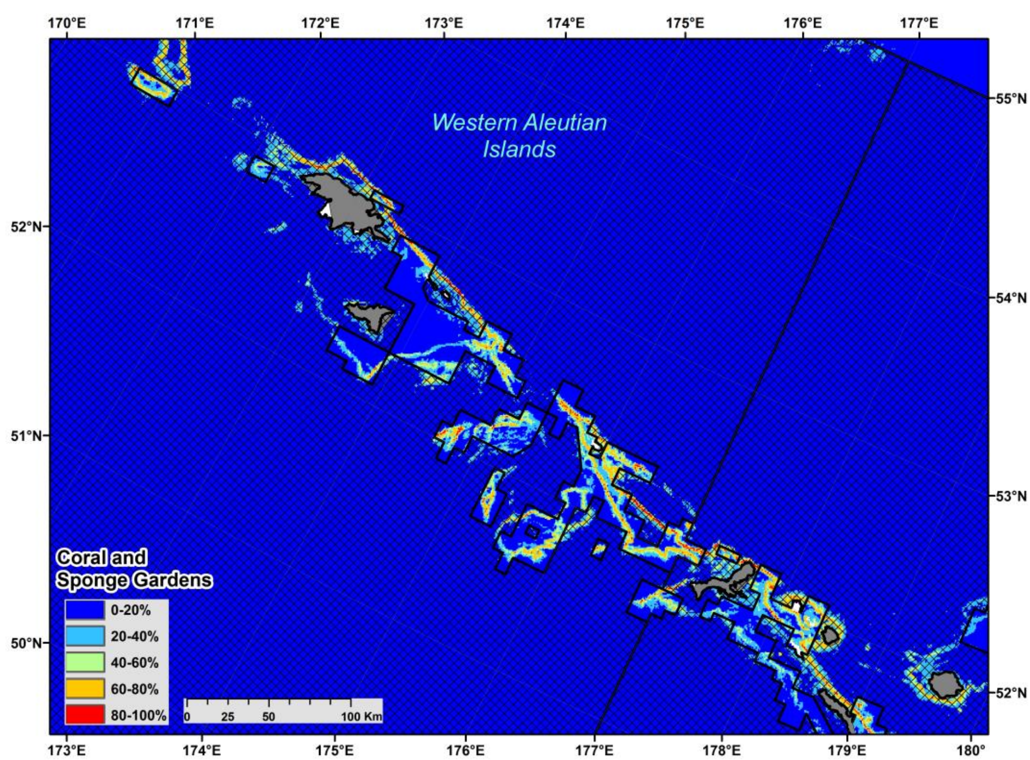

Figure 8. Maxent predictive habitat model results for coral and sponge gardens in the Western Aleutians with overlay of the Aleutian Island Habitat Conservation Area (bottom trawl closure is the black hatch).

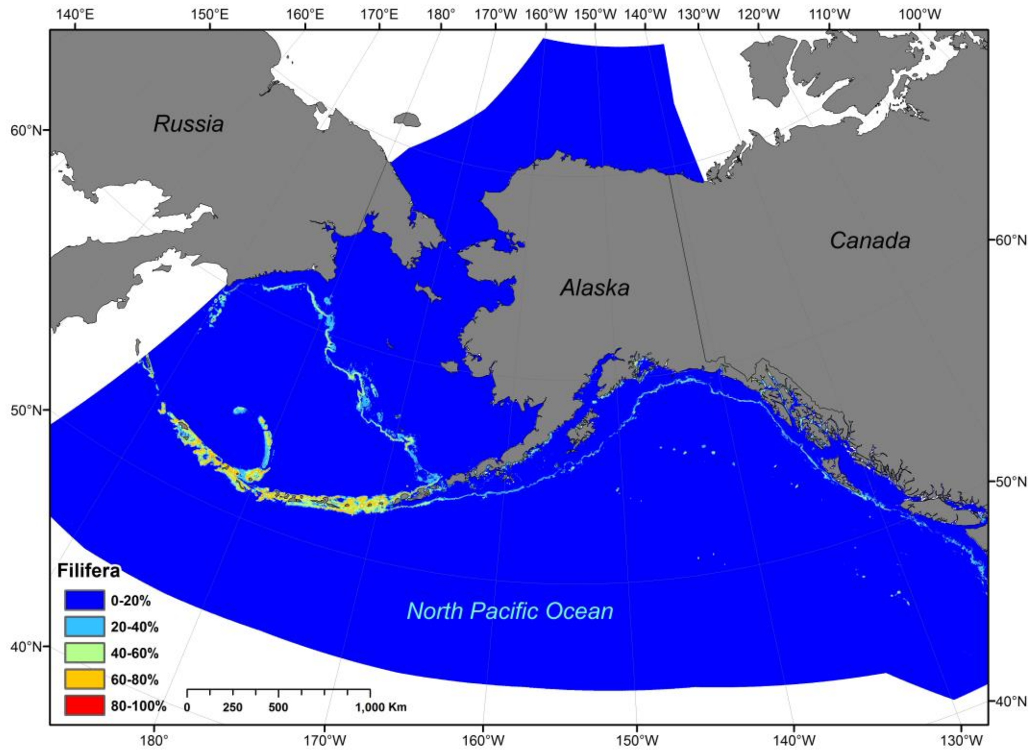

Figure 9. Maxent predictive habitat model results for Suborder Filifera.

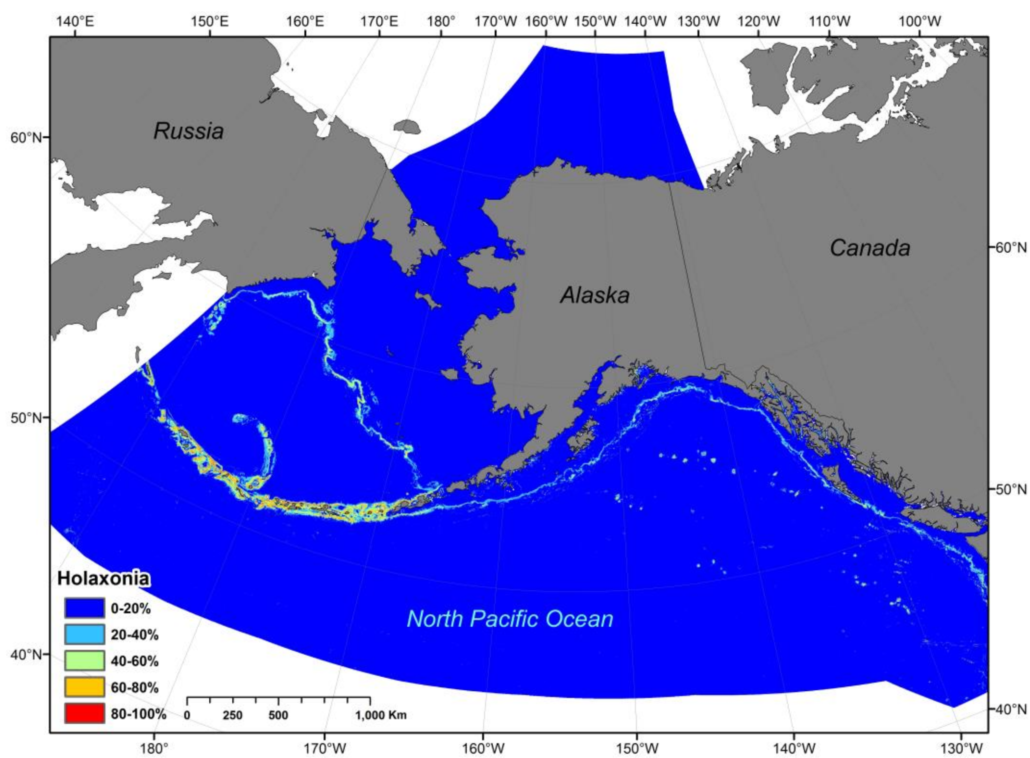

Figure 10. Maxent predictive habitat model results for Suborder Holaxonia.

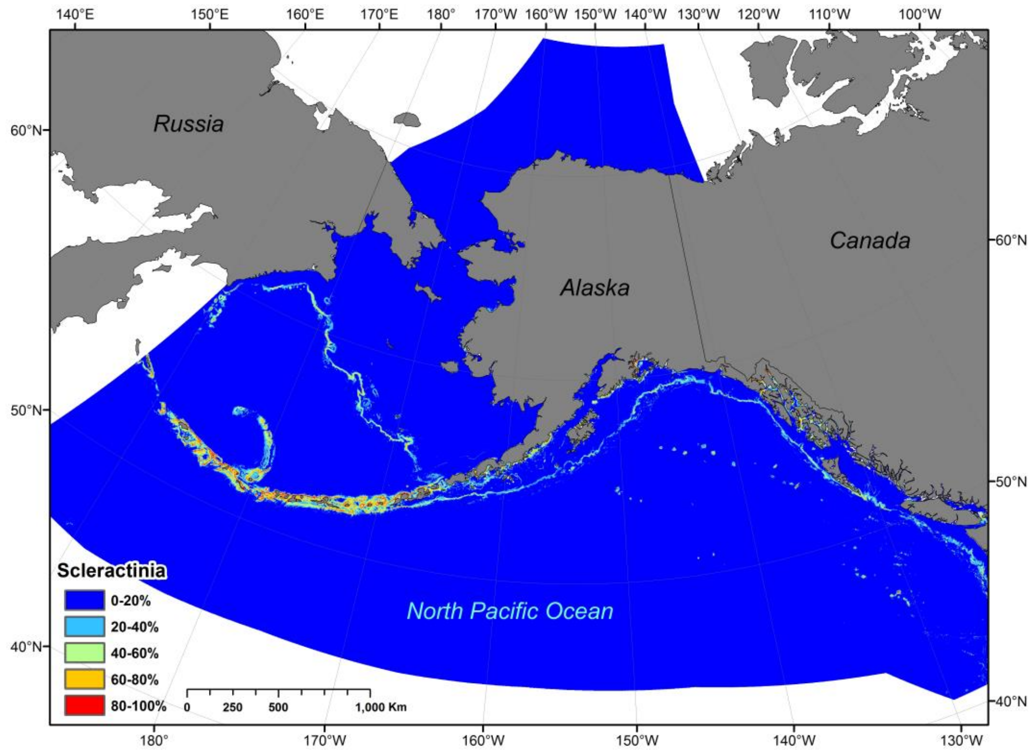

Figure 11. Maxent predictive habitat model results for Order Scleractinia.

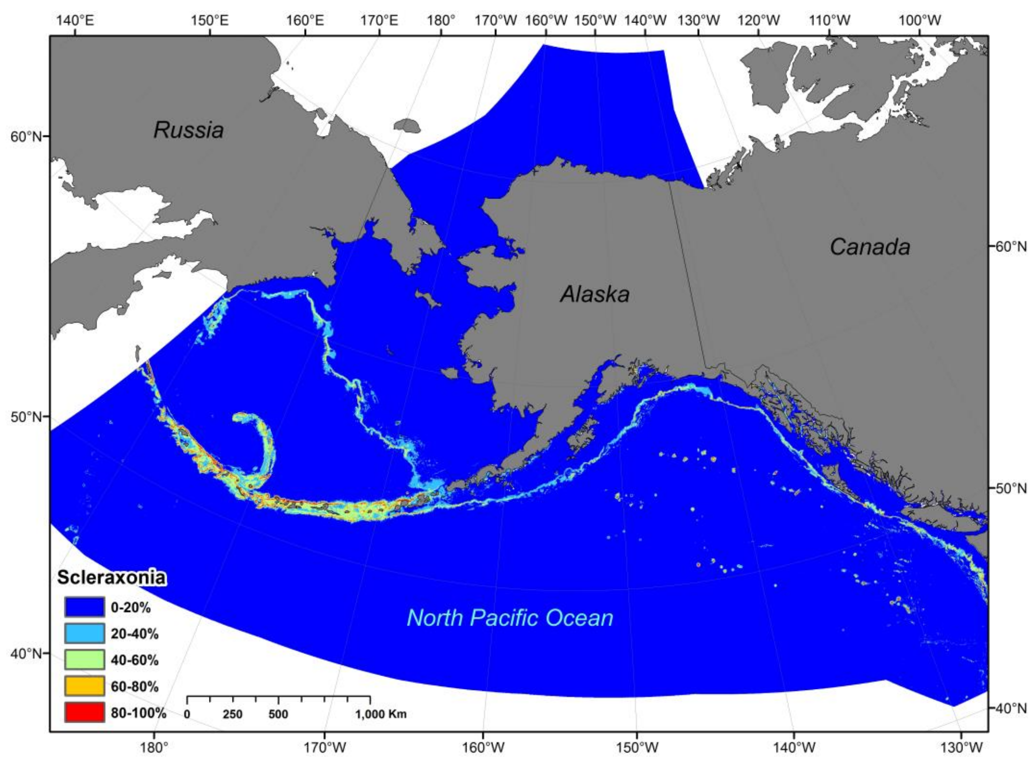

Figure 12. Maxent predictive habitat model results for Suborder Scleraxonia.

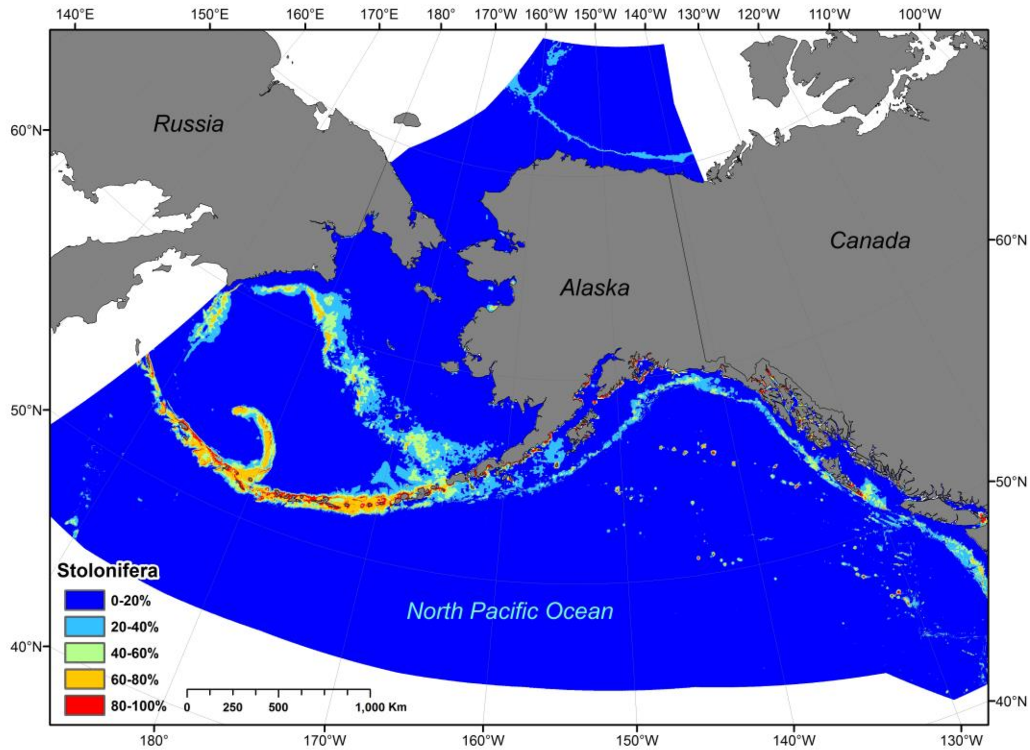

Figure 13. Maxent predictive habitat model results for Suborder Stolonifera.

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